

How New Yorkers Prefer to Take Public Transport?

A Comprehensive Analysis Based on 2010-2011 Regional Household Travel

Survey

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By

Yinan Tong

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Abstract

Public transport as a means of transport is an essential part of moving travelers from place to place. Considering the aggregate mode of travel, public transport is regarded as a more environmental friendly and sustainable travel mode compared to single occupancy vehicles travel.

I am interested to discover the exact factors on how built environment, individual characteristics and characteristics in travel could change mode choice preference in New York Metropolitan Area.

The 2010-2011 NYMTC Regional Household Travel Survey and 2010 ACS 5-year estimate data will be used to establish multinomial logit models to interpret the effects. From model results, both high population density and job density help to encourage more public transport trips. The effects of population density and job density only vary by trip purposes. Other socioeconomic and trip-based variables also play significant role on mode choice decisions.

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1. Introduction

With the introduction of Omnibuses, public transit expanded the accessible realm of humans quite a lot by providing a mode of higher mobility than walking. Before the popularization of private vehicles around 1950s, the public transit system went through a prosperous boom from horse cars to advanced bus and subway network. This formulated current high figure in transit mode share in New York City.

From the planning perspective, public transport is more favored so as to achieve a more sustainable development. Compared to private vehicles, the aggregate mode of travel by transit would incur less pollution and congestion. So it is now regarded as a more sustainable and environmental friendly mode of travel. However, the convenience of private vehicles did attract a lot of people and is extremely hard to let them switch to take a public transport now. In order to think about the strategies to attract more transit riders, I would like to study the mode choice patterns in New York metropolitan area, in which the public transport has a best performance among United States.

In the first part, I would provide a brief history of public transit development and a literature review on factors which might impact mode choice. Then I will introduce the data I would like to use, which is the 2010-2011 NY regional household travel survey. The third part would be the introduction of discrete choice modeling and its application in travel behavior research as I would like to take this as my major methodology to analyze the patterns of preference on transit. The travel modes will be categorized as private cars, public transport, and slow traffic (walk and bike).

I would study the trip data for single trip travel behavior. The variables planned to be selected are listed in the next section. The last part would be the discussion about why New York City could achieve a high level of transit ridership, corresponding recommendations from the results to sustain and improve public transit service and some indications for other US cities public transport improvement.

2. History of Public Transport in New York

There is a history of about 200 years for public transport in New York City. At the very beginning, the buses, elevated lines, commuter railroads were all operated by private entities as well as the later the most important New York City subways. The first underground line of the subway opened on October 27, 1904, almost 35 years after the opening of the first elevated line in New York City. Opening prices for a ride cost riders \$0.05 and in the first day alone carried over 150,000 passengers.

By the time the first subway opened, the lines had been consolidated into two privately owned systems, the Brooklyn Rapid Transit Company (BRT, later Brooklyn–Manhattan Transit Corporation, BMT) and the Interborough Rapid Transit Company (IRT). The city was closely involved: all lines built for the IRT and most other lines built or improved for the BRT after 1913 were built by the city and leased to the companies. The first line of the city-owned and operated Independent Subway System (IND) opened in 1932.

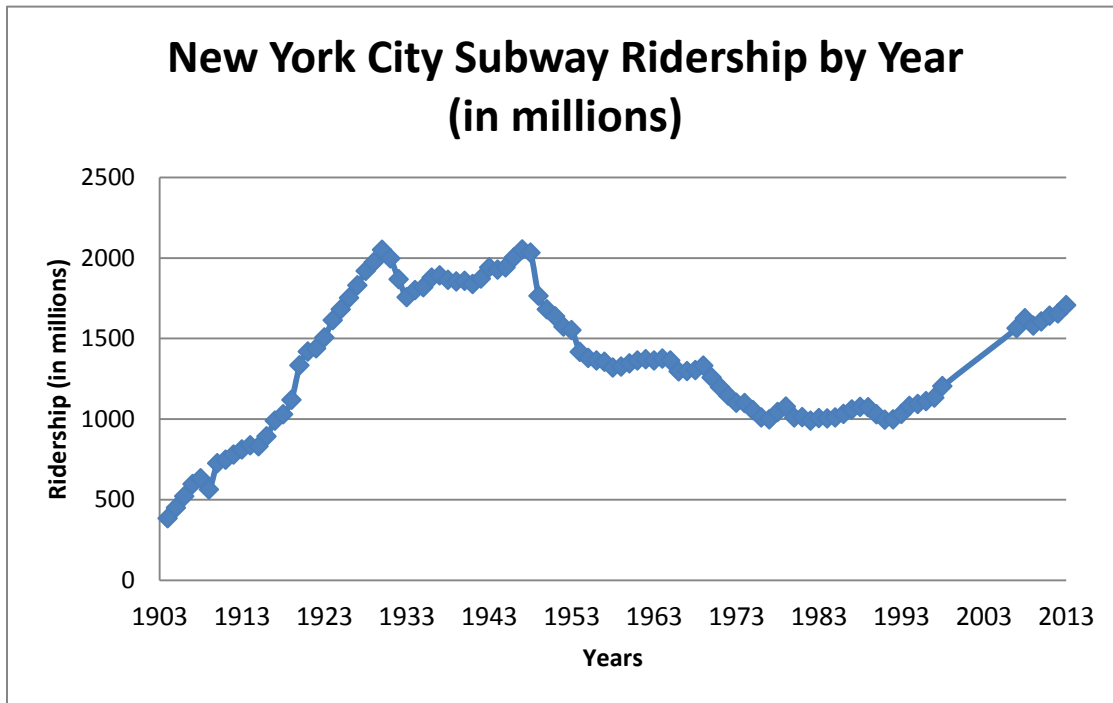


Figure 1: New York Subway Ridership by Year (1901-1997, source: Metropolitan Transportation Authority)

Before 1945, the end of World War II, the public transport system suffered rapid growth of ridership as it was the first choice of travel during that time and private vehicles were not yet popularized. From the chart above, the ridership experienced the sharpest growth during that period and reached its peak around 1945. The 30-year period after World War II was the darkest time for the public transportation. By the 1970s and 1980s, the New York City Subway was at an all-time low. In 1940, the two private systems were bought by the city and The New York City Transit Authority (NYCTA), a public authority presided by New York City, was created in 1953 to take over subway, bus, and streetcar operations from the city, and placed under control of the state-level Metropolitan Transportation Authority in 1968. Ridership had dropped to 1910s levels,

and graffiti and crime was rampant on the subway; in general, the subway was very poorly maintained during that time, with delays and track problems were common.

A number of factors contributed to public transport's decline during that period. Rising per capita incomes, together with the improved quality and reduced price of cars, led to rapid growth in auto ownership. At the same time, the urban and suburban roadway network expanded rapidly, further encouraging auto use and suburban living. More people shifted to more auto use and the drop of revenues for public transport contributed to a severe underfunding of those for-profit, private-owned public transport companies. Those companies did not receive government subsidies and nor were they heavily regulated by government (Altshuler, Womack, & Pucher, 1979). Their response to increased competition from the automobile was to raise fares, cut services, and delay maintenance and capital investment. These measures worsen the already deteriorating public transport market and finally went to the bankruptcy and the public take over.

Thanks to a huge infusion of government funds after the public takeover, the system began to be resuscitated. By the early 1990s, conditions had improved significantly, although maintenance backlogs accumulated during those 20 years are still being fixed today. The ridership also began growing again after a long cutback from 1945. As the system enters the 21st century, it continues to progress and form a stable trend of ridership growth despite any significant attacks. The September 11 attacks resulted in service disruptions on lines running through Lower Manhattan. In 2012, Hurricane Sandy wreaked havoc on the subway system, flooding several underwater tunnels and other vulnerable locations near New York Harbor. These huge attacks did not drop the

subway ridership too much. On the contrary, the Annual subway ridership of 1.708 billion in 2013 is now the highest since 1949, reaching 65-year high.

In addition to the subways as the major tools for intra New York City travel, the public transport in New York metropolitan region, Long Island Rail Road, Metro North Railroad, New Jersey Transit and Port Authority Trans Hudson (PATH) are all undergoing ridership growth these years. Metro-North's annual east of Hudson ridership in 2013 was the highest in the railroad's history, at 81.8 million, surpassing the previous east of Hudson record of 81.5 million rides that was set in 2008. The LIRR carried 83.4 million riders in 2013, an increase of 1,640,716 passengers over the previous year. NJ Transit officials reported total ridership for that one year period grew by 950,946, boosting yearly ridership from 45.48 million to 46.4 million. And PATH is also projected to break annual record these years.

Now it is a critical time for New York metropolitan to rethink about public transport as the first choice to daily commute with the record of rapid ridership growth these years. There are a lot of mater projects under construction such as Long Island Rail Road East Side Access connecting LIRR to the Grand Central terminal at Midtown East, the extension of 7 line subway to benefit the Westside Manhattan, and the new Second Avenue Subway to alleviate the huge burden on current Lexington Lines. In addition, Metro North is also planning to reroute to Penn Station. All of these new connections will enhance the interaction within this region, create more opportunities and let public transport more and more popular again.

3. Literature Review

The Institute of Transportation Development Policy proposed that ‘Around the world, private car ownership is not only the source of ever increasing traffic congestion, but also a growing cause of greenhouse gas emissions, air pollution, and mounting social disparities.’¹ As an alternative to private car, public transport provides more aggregate and less polluting way of travel. Research on how to improve public transport mode share from private car is a hot topic to achieve a more sustainable transportation system.

Ralph Buehler et al. (2009) provided a perspective from policy makers on how to achieve a more sustainable transportation system in United States. Instructive learnings can be borrowed from the successful policies in Germany that government shall set the right price of driving, integrate public transportation mode, create safe and complete slow traffic zone, etc. And it is remained to see travelers’ response (the change of travel behavior) towards these policies.

I am more interested in how travelers behave to choose which travel mode within different circumstances. There is a huge pool of literature built around tests of the hypothesis that socioeconomic characters, and land use patterns, lead to a particular travel behavior.

Narisra Limtanakool (2006) completed their research about the socioeconomic, land use and travel time factors on mode choice for longer distance trips in the Netherlands by using 1998 Netherlands National Travel Survey data. The analysis indicates that land use attributes and travel

¹ <https://www.itdp.org/what-we-do/public-transport/>

time considerations are important in explaining the variation in mode choice when controlling for the socioeconomic characteristics of travelers.

Consistently, previous literature had demonstrated that higher densities and mixed land uses characteristic of neighborhood developments are associated with reductions in private vehicle travel. Tim Schwanen et al. (2005) studied the factors of neighborhood physical structures on commute mode choice that the mismatch between a commuter's current neighborhood type and preferences regarding physical attributes of the residential neighborhood would cause more preference on private vehicle trips.

Earlier studies (e.g. Newman & Kenworthy 1989a, 1989b) exhibit that high-density urban forms are correlated with lower energy consumption and greater use of public transport, share ride, and walking. However, Wachs (1993) argued² that the current development trend even in very high-density cities such as Hong Kong and New York is toward lower densities and greater use of the automobile and that it is unreasonable to expect to "reverse steady, worldwide trend". Further, he pointed out that these high-density cities, while achieving lower vehicular and energy use per capita, the higher levels of congestion still exists precisely because of their higher density urban forms.

Among factors describing built environment, population and job densities are the two most frequently used variables for travel behavior research. Both have been found to be positively

² Wachs M, The role of land use strategies for improving transportation and air quality.

correlated with the number of non-vehicular trips in many studies. For example, using the 1996 Bay Area household travel survey, Reilly and Landis (2002) found that higher population density is correlated with higher probability of walking or taking public transit. On average, an increase in the average density of four persons per acre within one mile of an individual's residence is associated with a 7% increase in the probability of walking or taking transit. However, some other studies found the correlation between population density and transit trips negligible (Kockelman 1997; Miller and Ibrahim 1998).

Despite the evidence of impact from density, some researchers also doubt on that. Handy (1996) raised the doubt that whether it is the density or other factors (e.g., travel cost, travel time) going along with the density that truly cause travel behavior change. Miller (1998) argued that the impact of density is mediated through accessibility variables, based on the results of a study in the Toronto Area (Miller and Ibrahim 1998). They found that the distance to CBD is more correlated with daily vehicle kilometers traveled than density. In addition, Handy (1993) proposed measures of local and regional accessibility to shopping opportunities for 34 superdistricts in the San Francisco Bay Area. Using the 1981 Metropolitan Transportation Commission travel survey data, she analyzed shopping trips by geographic divisions, and concluded that high levels of either local and regional accessibility were associated with shorter trip lengths but not with fewer trips.

Apart from using accessibility variables to alleviate the impact of density, the impact of densities at either origins or destinations varies a lot. Frank and Pivo(1994) analyzed the travel modes between drive alone, public transit, and walking using the Puget Sound dataset in the Seattle area.

They showed that both job density at the destination and population density at the origin play roles in influencing mode choice decisions. Zhang (2004) found that higher population density at origin encourages the use of walking, biking, and transit for work trips but not for non-work trips, while higher population density at destination adds for both work and non-work trips. Higher job density at the origin is insignificant for both work and non-work trips while higher job density at the destination promotes the use of biking, walking, and transit for work trips but not for non-work trips.

Gordon et al. (1989) proposed that it is the spatial context, rather than density that explains travel behavior. The relationship between population density and travel time is ambiguous if the spatial structure is ignored. For example, the high densities in monocentric cities will definitely reduce trip distance while trip distances vary a lot in a polycentric city.

However, Weber and Kwan (2003) found that the impact of spatial context or density on individual accessibility is weak, much less than the influence of individual characteristics.

Actually there had been a lot of research indicating that individual characteristics played a role in travel behavior.

Prevedouros (1992) found that extroverts tended to make more non-work trips than introverts, that materialists tended to use a higher proportion of their incomes to buy a car than utilitarians, and that urbanites were more likely to live in higher-density areas than respondents having personalities more commonly associated with suburban living.

More recently, Kwan (2000) examined space-time patterns between different population segments (e.g., males vs. females) using their observed daily activity and travel patterns. She discovered that regardless of the employment status, women tend to consider at a higher level of space-time constraints and consequently have a lower level of individual accessibility to urban opportunities when compared with men.

Using a dataset collected from five neighborhoods in the San Francisco Bay Area, Kitamura et al. (1997) did a study to analyze whether land use, demographic and socioeconomic factors indeed affects travel. They found that attitudinal information played a more significant role in explaining travel behavior than transportation access related characteristics (built environment).

In addition to individual characteristics on a single trip travel behavior, the influence of tour complexity on mode choice decisions is a new topic as trip chaining is considered during a trip.

Ye et al. (2006) compared three possible correlations between trip chaining pattern and mode choice: trip chaining pattern is determined first and then influences mode choice; mode choice is determined first and then affects trip chaining pattern; and both are simultaneously determined.

Using the 2000 Swiss Microcensus Travel Survey, they found support for the first structure—that the determination of trip chaining pattern precedes mode choices.

While it is widely recognized that people chain their trips and today's trips have become far more complex than decades ago (Levinson and Kumar 1995), there are still far more mode choice studies focusing on single trips than those analyzing tours (Miller et al. 2006). Hanson and

Schwab (1986) found that unless the first trip in a tour is a trip to work, the mode choice of a tour is determined by all trips in a tour. The complexity of a tour is also found to have a negative influence on the choice of using mass transit (Toint and Cirillo 2001). In their work examining the space and time determinants of transit use in trip chains in Belgium, Vande Walle and Steenberghen (2006), the inability to use mass transit for a single trip in a tour prevented the person from using transit for remaining trip legs.

Most recently, controlling residential self-selection factor become a hot and critical method when taking analysis on built environment towards travel behavior. The test of this self-selection was carried out by a number of researchers. By controlling this self-selection factor through two-equation simultaneous system, Chen (2007) demonstrated that density, generalized travel cost, and access to transit stations all play roles on transit mode preference. However, another new concept, the tour level analysis was not much implemented in researches.

And developing from general linear regression, discrete choice modeling is now a popular method in researches on travel behavior (German, 2003; H.K. Lo et al., 2004; Zhan, 2008; Nir Sharaby, 2012). Using this method, researchers observe the behavior of an individual person, household at the micro level with described variables for choice from a set of mutually exclusive alternatives. (Moshe, 1985) The choice preference towards each alternative is based on the utility maximization theory. Lots of researches provided practical recommendations to improve public transport through different perspectives by using discrete choice analysis.

Based on that, I want to study the newly released 2010-2011 NY metropolitan regional household travel survey data, which is open to public at the end of 2013. Generally, by studying the new dataset, I want to generalize results why New York City has a large public transport share by the impact of socioeconomic variables, neighborhood characteristics and some service indicators of tour level travel. Finally I would like to provide practical recommendations towards improvement on public transport service to attract more people riding in the future.

4. Methodology

4.1 Multinomial Logit Model

Discrete choice analysis (multinomial logit model) will be implemented to analyze the mode choice propensity. From the Regional Household Travel Survey, I will categorize mode choice as to auto trips, railroad, subway, bus, and slow traffic which containing walking and biking.

Here are the equations for model. Normally the multinomial logit model nominates one of the response categories as a baseline or reference cell (here is the automobile trips), calculate log-odds for all other categories relative to the baseline, and then let the log-odds be a linear function of the predictors. The formula is as follows,

$$\ln \frac{p_{ij}}{p_i} = \alpha_j + \mathbf{x}_i \beta_j,$$

where α_j is a constant and β_j is a vector of regression coefficients, for $j = 1, 2, \dots, J-1$. Note that we have written the constant explicitly, so we will assume henceforth that the model matrix X does not include a column of ones. In the model, the probability distribution of the response is multinomial instead of binomial and we have $J-1$ equations instead of one. The $J-1$ multinomial logit equations contrast each of categories 1, 2, $J-1$ with category J , whereas the single logistic regression equation is a contrast between successes and failures. If $J = 2$ the multinomial logit model reduces to the usual logistic regression model.

The estimation method yields the coefficients, their asymptotic standard errors and respective

t-statistics. These statistics are useful to test the null hypothesis that a given coefficient is equal to zero. In addition to test the null hypothesis that all the parameters are zero a likelihood ratio test is performed. Other parameter typically reported is the measures ρ^2 which is analogous to the R^2 measure used in linear regression.

5. Data

The main dataset I want to use is NYMTC and NJTPA 2010-2011 Regional Household Travel Survey (RHTS). From the fall of 2010 through the fall of 2011, travel data was collected from nearly 19,000 households across 28 counties in New York, New Jersey and Connecticut, providing key travel statistics for the region to help in the planning of future transportation investments.

There are 28 counties in the metropolitan study area, which can be logically grouped into five sub-regions as follows and as shown in Figure 2-1:

1. New York City (NYC) – five boroughs comprised of Manhattan (New York), Queens, Bronx, Brooklyn (Kings), and Staten Island (Richmond) counties;
2. Long Island – Nassau and Suffolk counties;
3. Mid-Hudson Valley – Westchester, Dutchess, Putnam, Rockland and Orange counties;
4. New Jersey – Bergen, Passaic, Hudson, Essex, Union, Morris, Somerset, Middlesex, Monmouth, Ocean, Hunterdon, Warren, Sussex, and Mercer counties;
5. Connecticut – Fairfield and New Haven counties.



Figure 2: Regional Household Travel Survey Study Area (NYMTC & NJTPA)

In total, 143,925 linked trips were derived from 18,965 households and 43,558 participants, including a sub-sample of 1,930 households whose members provided travel data using wearable global positioning system (GPS) devices.

The independent variables I would like to study on are as follows.

- Socioeconomic

Age, Income Level, and Number of vehicles owned

- Built Environment

Population density, both at origin and destination

Job density, both at origin and destination

- Others

Trip distance, Trip travel time, Home Places, Trip purposes, Number of people in the trip

For socioeconomic variables, three most significant independent variables are selected in the

model for analysis. Age as we know, plays an important role on travel behavior. Here I

hypothesize that the elder the traveler is, the higher propensity on driving a car the traveler will

have. Income level is also a general measure of social status which as well will have impact on

travel behavior. And I hypothesize that the higher income level the travel is within, the higher

propensity on driving a car the traveler will have. More vehicles owned in a household will also

encourage the household members to drive more rather than take other alternatives for travel. I

here hypothesize that the more cars owned the higher propensity of driving a car as well.

For the variables indicating built environment, there are a lot of ways to present: population

density, job density, number of intersections, number of transit stops, etc. With the constraints of

data source and technical skills, I select the two most general used variables, population density

and job density for analysis. It is discovered that population density at origin and job density at

destination has the most significant effects on mode choice (Frank and Pivo, 1994). I will use this

as the base hypothesis and check as well the population density at both origin and destination by

classifying the trip purposes and the effects of job density as well.

The density at trip origins and destinations are not given from the Regional Household Travel Survey data set. The population data was obtained through 2009-2013 ACS 5-year estimate and the number of employments data was from 2011 County Business Patterns. With the help of Geographical Informational System software, the density at each zip code area was calculated by the geometric calculation function in ArcGIS with the input of zip code maps and the table containing population sizes, number of employments and their corresponding zip code. Then by tracing back on the RHTS's origin zip code and destination zip code column, the density of population and employments were joined to each trip record and then it is ready for running the model with density variables.

Trip distance is included in the model as I want to discover the upper and lower distance threshold of transit trips. I here hypothesize 1~10 miles as the normal range of most transit tips distance. Travel time will be used for estimating the value of time for each other independent variable. The number of travelers along one trip could also be a factor on mode choice. A group of over 5 would exceed the carrying capacity of a private car, which might contributes to a higher probability of use on public transport. And in the current situations single occupancy vehicle is the most contributor of road congestion, the least efficient way of travel and as well the most severe contributor of carbon footprint. So the groups of number of people in a trip will set as 1 person/trip, 2-5 persons/trip, and over 5 persons/trip. Trip purposes are classified as work trips, school trips, shopping, social and recreational trips and others given by the Regional Household

Travel Survey data.

Table 1 Descriptive statistics of independent variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Population Density at Origins	66418	23.67	39.17	0	529.71
Population Density at Destinations	66418	25.96	41.1	0	529.71
Job Density at Origins	66418	19.00	69.19	0	1993.53
Job Density at Destinations	66418	33.58	98.29	0	1993.53
Trip distance	66418	6.4	9.74	0	131.05
Household Vehicles	66418	1.71	0.95	0	3

From the report of Regional Household Travel Survey, there are some basic analyses about mode choice behavior. The following chart shows the distribution of primary mode used for all trips including all study area from the 1997/1998 and 2010/2011 survey. The choice in mode of travel has not changed greatly from the 1997/1998 survey. Because of including the suburban areas in this region, the travel mode is still dominated by the automobiles, at a share of over 66%, although there are fewer auto passenger trips than in 1997/1998. Public Transport, both bus and rail together only has a share of 15% in total trips and it is even decreasing between these 10 years and smaller than the share of walk/bike trips (17.5%). Travelers make slightly more walk trips in the 2010/2011 survey.

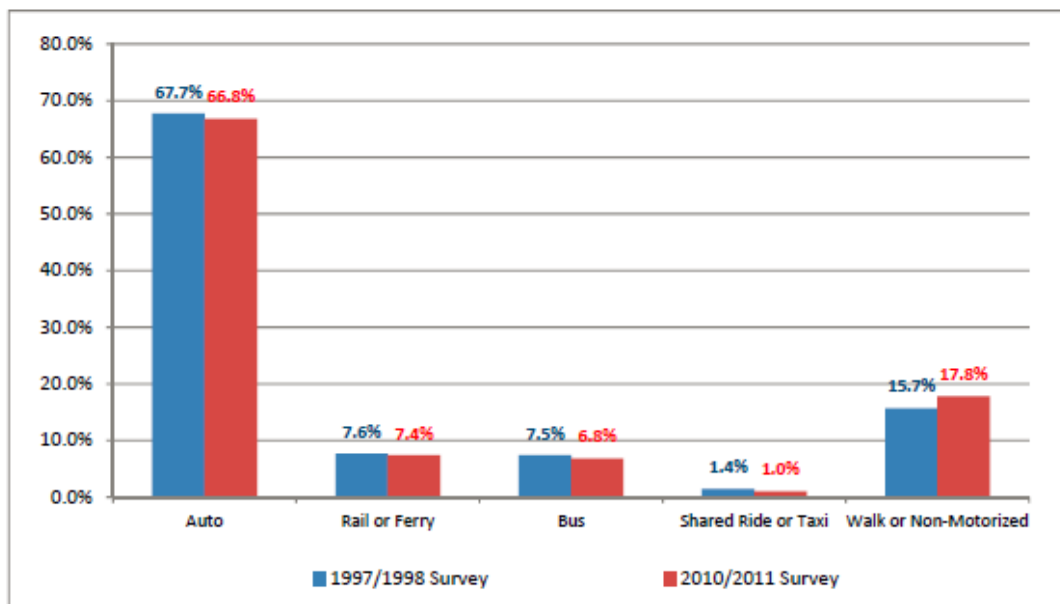


Figure 3 Primary Mode Used for All Trips (NYMTC & NJTPA)

The report also provided a chart about the mode choice distribution based on destination locations.

As expected, Manhattan, the other New York City boroughs and the urbanized areas of Hudson

County in New Jersey had the highest percentages of non-motorized trips within their physical

boundaries (56%, 32% and 31%, respectively). Except for Brooklyn, Queens, Manhattan and the

Bronx, Hudson County is the only county in the study area with an auto mode share less than 70%

(with 47% of trips by auto), a non-motorized mode share greater than 25% (with 31% of trips

using non-motorized means) or a rail/ferry mode share greater than 5% (with 11% of trips via

rail/ferry). Manhattan shows a unique mode share pattern with the rail as the highest use of mode

choice. Other NYC destinations also indicate a higher rail use as well. Then place specific

considerations will be necessary for the further analysis on the travel behavior.

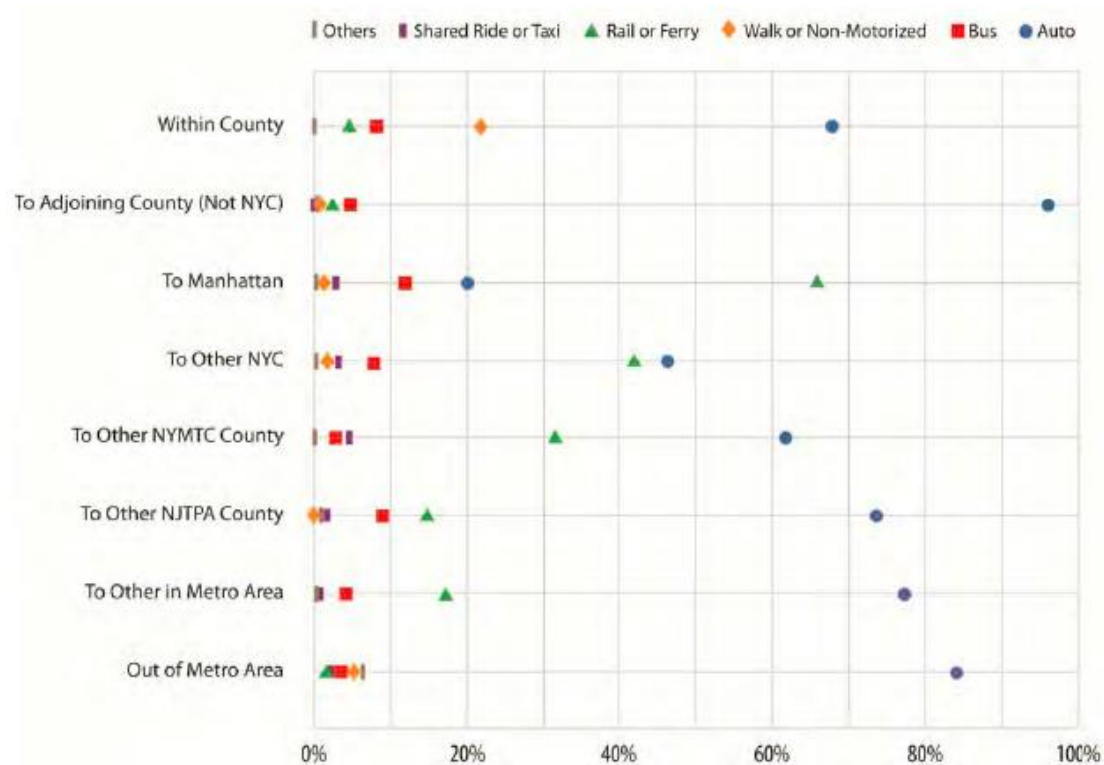


Figure 4 Primary Mode Used for Each Destination Location (NYMTC & NJTPA)

The charts above analyzed the general mode choice pattern within each district of the region and I want to discover what factors are causing these great differences of mode choice and it is discussed in the next chapter.

6. Multinomial Logit Model Analysis

6.1 Model including the whole region by departure time

First, I run the general model including the whole region with the dependent variables set as automobile, public transport and walking/biking. The chart below shows the mode share varying by places. Manhattan and other boroughs in NYC show great difference of usage between bus and rail and there is not such a big difference for other places. Based on this, it is simpler to just consider public transport as a whole category rather than specifically for bus and rail for the whole region. Further on I will study the difference between bus and rail in a model for specific areas.

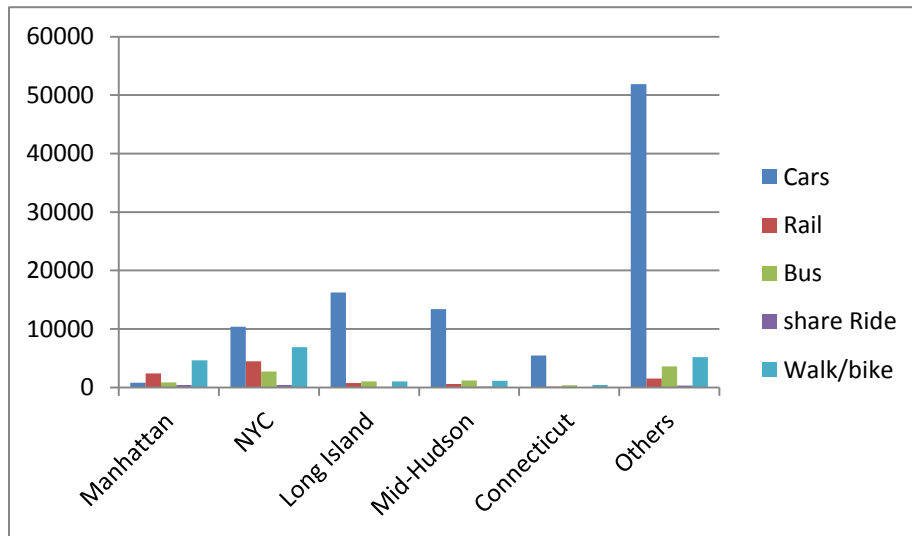


Figure 5 Mode share in each area (NYMTC & NJTPA, 2010-2011 Regional Household Travel Survey)

Because of considering density variables at both origins and destinations, the model is separated into two parts AM/PM by the departure time since in the big general model most AM trips origins will be counted as destinations for PM trips, which will counteract the particular effects of trip origins or destinations. Therefore, the two models are set as AM model for trips departing from 12 am to 12 pm and PM model for trips from 12pm to 12 am.

Population is counted by the residents' origin so that population density only refers to the density at home place. And job density only refers to the density at work place as it is counted for the workplace. Based on this, population density at origin and job density at destination in AM model shall have more significant effect and vice versa for the PM model.

Apart from density variables, other independent variables like age, trips start at home or not, trip distance, number of people along a trip, household income level and owning a car or not are included in the model as they are assumed with significant effects on mode choice decision. Trip distance variable is separated into three groups: 0-1 mile for walking/biking, 1-10 mile for transit, and over 10 miles. Number of people along a trip is also categorized as single occupant trip, 2-5 people with correspondence to the carrying capacity of a private vehicle and over 5 people.

Table 2 Multinomial logistic regression of mode choice by departure time

Base Mode: Auto	AM			PM		
	Relative Risk Ratio	Standard Error		Relative Risk Ratio	Standard Error	
Mode: Transit						
Age	0.541	0.0052	**	0.519	0.0057	**

Home as O/D		1.540	0.0593	**	1.646	0.0690	**
Population density at origin	Base: 0~20/acre						
>100		1.477	0.1329	**	4.118	0.3408	**
20~100		1.407	0.0688	**	3.423	0.1826	**
Population density at destination	Base: 0~20/acre						
>100		3.608	0.2818	**	2.150	0.2018	**
20~100		3.150	0.1546	**	1.949	0.1046	**
Job density at origin	Base: 0~20/acre						
>100		1.622	0.1784	**	22.496	1.7081	**
20~100		1.130	0.0831		4.594	0.2899	**
Job density at destination	Base: 0~20/acre						
>100		27.448	1.8959	**	3.124	0.3586	**
20~100		4.841	0.2842	**	1.107	0.0865	
Trip Distance	Base: >10 miles						
0~1 mile		0.286	0.0616	**	0.218	0.0145	**
1~10 miles		1.855	0.3729	**	0.718	0.0337	**
Number of people in a trip	Base: single Trip						
2~5 people		0.244	0.0098	**	0.113	0.0052	**
over 5 people		0.858	0.0530	**	4.950	0.4422	**
Income group		0.925	0.0141	**	0.917	0.0157	**
No cars in household		22.018	1.2280	**	18.589	1.1509	**
Constant		0.550	0.1163	**	1.371	0.1240	**
<hr/>							
Mode: Walk/Bike							
Age		0.722	0.0077	**	0.708	0.0071	**
Home as O/D		1.165	0.0468	**	1.205	0.0484	**
Population density at origin	Base: 0~20/acre						
>100		2.476	0.2731	**	3.059	0.3669	**
20~100		2.178	0.1586	**	2.330	0.1950	**
Population density at destination	Base: 0~20/acre						
>100		2.394	0.2518	**	2.839	0.3490	**
20~100		2.084	0.1512	**	2.136	0.1792	**
Job density at origin	Base: 0~20/acre						
>100		5.148	0.6064	**	8.400	1.0004	**
20~100		2.358	0.1950	**	2.332	0.2165	**
Job density at destination	Base: 0~20/acre						
>100		7.354	0.7005	**	6.543	0.9255	**
20~100		2.619	0.2036	**	2.045	0.1971	**
Trip Distance	Base: >10 miles						

0~1 mile	5.641	0.9311	**	82.955	11.3977	**
1~10 miles	0.168	0.0278	**	1.867	0.2670	**
Number of people in a trip	Base: single Trip					
2~5 people	0.385	0.0169	**	0.281	0.0118	**
over 5 people	0.294	0.0288	**	0.474	0.0709	**
Income group	0.927	0.0158	**	0.905	0.0151	**
No cars in household	19.139	1.1763	**	17.183	1.0933	**
Constant	0.441	0.0800	**	0.020	0.0031	**
Observations	66418			61643		
L(0)	-50453.715			-48059		
L(B)	-24477.122			-21847.6		
-2[L(0)-L(B)]	51953.186			52422.64		
LR test p value	0			0		
Pseudo R ²	0.5149			0.5454		

In the models above, the coefficients are represented by the relative risk ratio (RRR) which indicates the ratio of probability on using this kind of mode to travel compared to the probability on using automobile to travel based on this specific independent factor. For example, in the AM model, the RRR of Home as O/D variable as 1.540 indicates that when controlling other variables, when people start or end their trips at home, the ratio on the probability of taking public transport to the probability of taking automobile trips is 1.540 times than the ratio for those trips not related to home compared to auto trips.

Both two models indicate a valid result by its LR test p value as 0.000 and a Pseudo R² over 0.5. The coefficients for each independent variable have a 95% statistical significant level except for the job density at 20-100 per square kilometers at origin. This indicates that not both job and population densities at both origin and destination have the same statistical level of effect on the mode choice.

For the density variables, the model result is not consistent with the hypothesis that population density at home and job density at work places have stronger effects. It shows that both population and job density at destination in AM model and origin in PM model have much higher contributions on encouraging public transport trips. This shows that density at origins or destinations may not be a dominant factor on more public transport selections. And a speculation for this could be the commute pattern in this region that home at outside low density area and work place in Manhattan. Destinations in AM trips and Origins in PM trips all refers to the high density Manhattan area. From this result, I hypothesize that regardless of trip origins or destinations, the higher density at Manhattan actually contributes to higher probability for public transport trips.

The only difference between these two models above is the switch of origins, destinations from AM to PM. From comparison of the results of these two models, other variables than density show consistent coefficient values with same statistical significant level. Therefore other factors are consistent regardless of when the trips are traveled.

For simplicity, I select the AM model for interpreting. Among other variables, no cars dummy variable contributes the highest probability of choosing public transport for travel with a 22.018 times relative risk ratio. This is reasonable that a person without a car might not travel mostly by renting a car. And the person might not be able to walk for all trips which may have a quite long distance.

Age variable has an effect that by stepping into an elder age group, the probability to take public transport is 0.541 times as the previous age group, which shows that elder people are less willing to take public transport. This also conforms to the trend that the generations growing up with the popularization of private cars are getting older now.

Trips start or end at home have a 1.540 relative risk ratio. This can be understood as people are more familiar with the environment around home and are more willing to take the public transport with the higher reliability from their own knowledge.

The two trip distance dummy variables conform well to the two hypotheses. First, people will not probably take a public transport for a travel distance within 1 mile as the model results show that compare to trips over 10 miles, trips within 1 mile has a 0.286 relative risk ratio. Second, trips between 1 and 10 miles is the favorable threshold for a public transport travel with a 1.855 relative risk ratio compared to trips over 10 miles.

The income level from the results contributes slightly to the preference between public transport and private cars. The 0.925 relative risk ratio means by stepping into a higher level of income group, the willingness of taking public transport would be almost 0.925 times compared to the previous group. This also conforms to the fact that regardless of income, most people in New York City take public transport to work.

6.2 Models specified by places

As from Figure5 above, the mode share at each place within this region varies quite a lot, it is necessary to analyze the scenarios at each different place and check if built environment and socioeconomic variables play different roles in each place. The place groups are set by the surveyee's home place. Based on the mode share patterns, three place groups are set as Manhattan, other four boroughs in New York City (NYC) and other places in the region. Manhattan is the highest density hub of the region and it has the reverse trend of mode share from high to low as walking/biking, transit and automobiles. Other 4 boroughs of New York City are in transition place of the mode share distribution between Manhattan and outer places. It is also worth being set up as an individual group to study. The remaining other places share similar mode choice patterns dominated by automobiles so that they are set as a same group together.

Table 3 Models by specific place

Base Mode: Auto	Manhattan			NYC			Others		
	Relative	Standard		Relative	Standard		Relative	Standard	
	Risk Ratio	Error		Risk Ratio	Error		Risk Ratio	Error	
Mode: Transit									
Age	0.884	0.0214	**	0.665	0.0089	**	0.446	0.0044	**
Home as O/D	0.907	0.0853		1.469	0.0754	**	1.707	0.0664	**
Population density	Base: 0~20/acre								
>100	2.48E+07	2.07E+10		4.071	0.4380	**	3.649	0.3284	**
20~100	2.57E+07	2.15E+10		3.168	0.2956	**	2.518	0.1199	**
Job density	Base: 0~20/acre								
>100	3.531	0.4620	**	16.640	1.2189	**	77.661	5.8057	**
20~100	2.133	0.2772	**	3.179	0.1809	**	6.830	0.4360	**

Trip Distance	Base: >10 miles								
0~1 mile	0.590	0.0910	**	0.168	0.0144	**	0.370	0.0210	**
1~10 miles	2.664	0.3276	**	0.760	0.0465	**	0.915	0.0386	*
Number of people in a trip	Base: Single Trip								
2~5 people	0.199	0.0187	**	0.173	0.0092	**	0.147	0.0056	**
over 5 people	0.440	0.1896	*	0.877	0.1671		5.930	0.4206	**
Income group	0.898	0.0338	**	0.838	0.0182	**	0.993	0.0153	
No cars in household	3.964	0.3439	**	17.164	1.0613	**	34.729	2.3319	**
Constant	0.000	0.0000		1.163	0.1653		1.202	0.0979	*
<hr/>									
Mode: Walk/Bike									
Age	0.842	0.0235	**	0.800	0.0103	**	0.727	0.0062	**
Home as O/D	0.952	0.0977		1.121	0.0567	*	1.086	0.0372	*
Population density	Base: 0~20/acre								
>100	18.994	8.1021	**	3.296	0.3335	**	4.349	0.6025	**
20~100	26.399	11.3410	**	2.756	0.1934	**	2.388	0.1118	**
Job density	Base: 0~20/acre								
>100	2.734	0.3977	**	8.018	0.8214	**	34.507	3.9580	**
20~100	1.741	0.2452	**	2.093	0.1415	**	5.430	0.4212	**
Trip Distance	Base: >10 miles								
0~1 mile	63.289	11.7399	**	60.566	8.9130	**	251.963	39.0932	**
1~10 miles	1.478	0.2754	*	1.298	0.1975		5.041	0.8043	**
Number of people in a trip	Base: Single Trip								
2~5 people	0.334	0.0353	**	0.300	0.0156	**	0.344	0.0124	**
over 5 people	0.135	0.0667	**	0.123	0.0331	**	0.546	0.0746	**
Income group	1.044	0.0447		0.996	0.0218		0.874	0.0125	**
No cars in household	3.435	0.3391	**	16.225	1.1070	**	24.917	1.6634	**
Constant	0.012	0.0057	**	0.024	0.0046	**	0.007	0.0011	**
<hr/>									
Observations	8447			23826			97634		
L(0)	-8244.3035			-25637.276			-54271.2		
L(B)	-4234.7536			-12941.393			-29686.5		
-2[L(0)-L(B)]	8019.1			25391.77			49169.32		
LR test p value	0.000			0.000			0.000		
Pseudo R ²	0.4863			0.4952			0.4530		

Among the three models in each place, age variable exhibits a consistent trend that the older the traveler, the less probability he will take public transport for travel. No cars dummy variable is similar in consistency that it leads to more public transport trips. The ascending relative risk ratio ranking for not owning a private car is Manhattan, NYC and then other places. This indicates that

Manhattan as a place with much higher density has a higher flexibility of travel mode selections which disperse the effects of even as not owning a car.

The dummy variable of whether trip starts or ends at home result conforms to the general model and shares a similar relative risk ratio around 1.5 for other NYC and outer areas.

The effect of difference between household income levels can be skipped since it is a statistical insignificant result for the other place group and the ratio itself is smaller compared to any other factor. Therefore household income does not execute a major impact on the mode choice all over the whole region.

The results of density variables show that the lower density a traveler live with, the higher job density would have more significant effect on public transport use. In the model of Manhattan, population density variable gets a statistical insignificant coefficient and job density coefficient is not big as well. The relative risk ration for the model in NYC is also smaller compared to other places. Among all three models, it is consistent that high job density contributes more than high population density does to public transport trips.

From here two trends can be concluded: (1) High density built environment only has effect to encourage more public transport use at a place which is generally with low density; (2) High job density encourages more public transport trips than high population density does. Trip distance and Number of people along a trip do not have significant consistent patterns by places.

6.3 Models to compare bus and rail

In the New York Metro region, bus and railroad are two major modes of public transport. For the simplicity of analysis on general model, the specific bus and rail modes are combined as one option---public transport into consideration. Here I select New York City and Long Island, the two places which both have a high coverage rate of bus and rail network but differ from the density for comparison. The results of this model might be helpful for specific development on bus or rail.

Table 4 Models comparing rail and bus to auto trips in NYC and Long Island

Base Mode: Auto	NYC			Long Island		
	Relative Risk	Standard		Relative Risk	Standard	
	Ratio	Error		Ratio	Error	
Mode: Rail						
Age	0.906	0.0143	**	0.941	0.0579	
Home as O/D	1.159	0.0682	**	0.929	0.1578	
Population density	Base: 0~20/acre					
>100	3.289	0.7778	**	13.562	3.5729	**
20~100	3.613	0.8347	**	10.325	2.1813	**
Job density	Base: 0~20/acre					
>100	3.705	0.2863	**	86.114	18.6444	**
20~100	2.441	0.1701	**	18.505	3.7750	**
Trip Distance	Base: >10 miles					
0~1 mile	0.001	0.0001	**	0.009	0.0090	**
1~10 miles	0.635	0.0709	*	0.168	0.0352	**
Number of people in a trip	Base: Single Trip					
2~5 people	0.516	0.0333	**	0.249	0.0466	**
over 5 people	0.957	0.3385	**	0.000	0.0004	
Income group	0.885	0.0216	**	0.867	0.0736	
No cars in household	1.190	0.0742	**	34.816	15.5166	**
Constant	3.264	0.8956	**	0.025	0.0120	**

Mode: Bus						
Age	0.843	0.0124	**	0.317	0.0106	**
Home as O/D	1.175	0.0695	**	1.929	0.2394	**
Population density	Base: 0~20/acre					
>100	0.676	0.0849	**	5.790	4.3405	*
20~100	0.769	0.0875	**	1.134	0.2799	
Job density	Base: 0~20/acre					
>100	0.610	0.0484	**	1.595	1.2818	
20~100	0.736	0.0502	**	0.302	0.2677	
Trip Distance	Base: >10 miles					
0~1 mile	0.011	0.0014	**	1.608	0.3253	*
1~10 miles	1.047	0.1265	**	2.535	0.4788	**
Number of people in a trip	Base: Single Trip					
2~5 people	0.602	0.0384	**	0.106	0.0111	**
over 5 people	9.937	2.2305		8.470	1.5071	**
Income group	0.744	0.0188	**	0.974	0.0467	
No cars in household	0.980	0.0603	**	179.487	48.5533	**
Constant	26.938	5.1553	**	0.971	0.2703	
Observations	32273			17933		
L(0)	-44555.674			-10725.659		
L(B)	-23984.249			-5291.1075		
-2[L(0)-L(B)]	41142.85			10869.1		
LR test p value	0.000			0.000		
Pseudo R ²	0.4617			0.5067		

From the model above, the bus service is less attractive than railroad for both Long Island and New York City travelers. Whether the trips start or end at home or not does not affect the choice between bus and rail in New York City and Long Island with a relative risk ratio close to 1. When considering trip distance, bus is much more attractive in both two places for trip distance less than 10 miles compared to rail.

The most significant differences between bus and rail come from the density factors. Both high population density and job density in New York City and Long Island attract more railway riders than bus passengers. The relative risk ratios in either NYC or Long

Island model are about three times for rail road than the one for bus. For rail road, both two models show that a population density over 20 per acre would support more public transport trips than automobiles and the even higher density does not contribute more while for job density, a place over 20 employees per acre already support rail road use and it is even the higher the better of the effect. The high density built environment works with a slighter effect than railroads encouraging bus trips.

6.4 Models specified by trip purposes

Table 5 Models specified by trip purposes

Base Mode: Auto	Work & School			Recreation & Shopping			Others		
	Relative	Standard		Relative	Standard		Relative	Standard	
	Risk Ratio	Error		Risk Ratio	Error		Risk Ratio	Error	
Mode: Transit									
Age	0.432	0.0049	**	0.858	0.0163	**	0.689	0.0102	**
Home as O/D	1.584	0.0632	**	0.912	0.0845		1.007	0.0521	
Population density	Base: 0~20/acre								
>100	3.258	0.2119	**	22.425	2.6334	**	8.438	0.7887	**
20~100	3.023	0.1287	**	12.017	1.0366	**	5.303	0.3403	**
Job density	Base: 0~20/acre								
>100	41.092	2.5348	**	16.646	1.8958	**	13.397	1.2599	**
20~100	5.879	0.3214	**	3.349	0.3089	**	3.681	0.2808	**
Trip Distance	Base: >10 miles								
0~1 mile	0.389	0.0233	**	0.172	0.0212	**	0.272	0.0257	**
1~10 miles	1.114	0.0440	**	0.749	0.0664	**	0.895	0.0675	
Number of people in a trip	Base: Single Trip								
2~5 people	0.208	0.0090	**	0.264	0.0191	**	0.193	0.0113	**
over 5 people	9.254	1.0307	**	2.205	0.5693	**	5.105	0.6716	**
Income group	0.982	0.0154		0.678	0.0207	**	0.814	0.0193	**
No cars in household	19.844	1.3640	**	14.903	1.1991	**	18.199	1.2179	**
Constant	2.241	0.1917	**	0.136	0.0248	**	0.348	0.0455	**
Mode: Walk/Bike									
Age	0.615	0.0091	**	0.811	0.0105	**	0.795	0.0086	**
Home as O/D	0.980	0.0505		1.070	0.0733		0.933	0.0359	
Population density	Base: 0~20/acre								
>100	4.216	0.3967	**	8.982	0.9676	**	6.569	0.5666	**
20~100	3.555	0.2021	**	4.688	0.2485	**	3.937	0.1747	**
Job density	Base: 0~20/acre								
>100	27.863	2.5830	**	7.573	1.0591	**	11.429	1.2071	**
20~100	4.072	0.3804	**	2.869	0.2615	**	3.673	0.2622	**
Trip Distance	Base: >10 miles								
0~1 mile	257.184	37.2561	**	50.928	7.8283	**	67.048	10.9989	**

1~10 miles	4.684	0.6905	**	1.185	0.1898		1.144	0.1970	
Number of people in a trip	Base: Single Trip								
2~5 people	0.219	0.0130	**	0.364	0.0149	**	0.411	0.0172	**
over 5 people	0.332	0.0760	**	0.232	0.0634	**	0.842	0.1420	**
Income group	0.985	0.0212		0.872	0.0183	**	0.931	0.0162	**
No cars in household	22.873	1.9111	**	11.958	0.9104	**	17.070	1.0978	**
Constant	0.010	0.0019	**	0.026	0.0049	**	0.013	0.0023	**
Observations	49171			32662			48074		
L(0)	-43286.372			-23607.475			-31948.8		
L(B)	-20575.495			-10029.1			-15206.5		
-2[L(0)-L(B)]	45421.75			27156.75			33484.71		
LR test p value	0.000			0.000			0.000		
Pseudo R ²	0.5247			0.5752			0.524		

From the three models by trip purpose above, the difference between trip purposes are most related to density effects and number of people along a trip. In work/school trips, it is still high job density area that encourages more public transport use. The place with a job density over 100 per acre is over 13 times on relative risk ration than the same level of population density plays. It also shows that the population density over 100 per acre has less difference on the effect of attracting more public transport use compared to population density between 20 and 100 per acre. In recreation and shopping trips, it is high population density rather than high job density that has more significant effect on attracting more public transport use (22.425 compared to 16.646). These discretionary trips exhibit totally different trends from commute trips. The result is also reasonable since people usually go shopping from their home rather than from work places. For trips by other purposes, high population density and high job density show a similar level of effect on the mode choice. And here in the rest of two groups it does not show a ceiling effect on high population density on attracting more public transport rides which appears

in the work/school trips.

The number of people in a group also has different effects on mode choice by trip purpose. For work/school trip, groups over 5 are much more willing to take public transport to commute. For other trip purposes, groups over 5 also show a preference on public transport but the coefficient is much smaller than the one for work/school trips.

7. Conclusion and Discussion

The results of discrete choice modeling conforms to existing literature that when controlling socioeconomic variables, built environment such as density and travel distance considerations have major impacts on mode choice (Narisra Limtanakool, 2006; Newman & Kenworthy 1989a, 1989b;).

The effects of population and job density execute a complex factor on mode choice travel behavior. Both population and job density in New York metropolitan region has strong impact on the preference on taking more public transport (Reilly and Landis, 2002). And the results exhibit that regardless of trip origins or destinations, either place with a higher population density or job density has a more significant effect on encouraging public transport use. This is a unique finding that is inconsistent with previous studies in other areas. Frank and Pivo, 1994 found that in Seattle, only job and population density at origins play a role on mode choice. Zhang, 2004 found that in Hong Kong, higher population density at origins and destinations, higher job density only at destinations has great impact on promoting public transport use.

This unique finding in New York might ascribe to its sharp change of density from city center to outer rings. The average job density over the whole region is around 37.5 jobs per acre while for the highest job density at central Manhattan jumps to almost 2000 jobs per acre. This sharp gap of densities between origins and destinations leads to a strict circumstance that it is not convenient

to drive a car to a place with a quite high density. Then it is reasonable that neither origin nor destination density has its own corresponding effects on the mode choice travel behavior.

Table 3 Summary of population density and job density

	Observations	Mean	Std. Dev.	Min	Max
population density	138278	30.5	46.9	0	529.7
job density	138278	37.5	104.4	0	1993.5

For the comparison of role between population density and job density, the results exhibit that either generally or by each specific place higher job density plays a more significant role than population density in New York Metro. This can also be attributed to the higher job density difference than population density in this area. The maximum job density is over 3 times the maximum population density. Based on these figures, there might be a threshold for extreme high job density area that is totally not friendly to private cars, for example, with narrow streets of serious congestion, lack of parking space, high parking price, etc. This worth further study and shall raise the planning concern on providing reliable public transport travel alternatives.

By setting both medium density and high density dummy variables, I found an interesting trend that in some cases population density has a ceiling effect that a place with a 50 residents per acre has a similar effect on encouraging public transport use than a place with a 200 residents per acre. NYC subset of the model specified by places, both places for model comparing bus and rail, and the model containing work and school trips exhibit this. This might ascribe to a potential factor for a population density over a certain level to encourage more public transport use like the

accessibility of rail road, the rigid demand by public transport for work trips, and New York City residents' overall attitudes on taking more buses than self-driving. This is also worth concern for a further study.

For the model comparing the effects of socioeconomic and built environment on choice of bus and railroad towards automobile trips, almost every factor exhibits a larger coefficient on railroad than bus. Commuter rails and subways are the dominant means of public transport in New York Metro.

The effects of population density and job density vary by specific trip purposes. For work & school trips the job density is more important than population density and the effect is opposite for recreation & shopping trips. And for other trips there is no significant difference between population density and job density. This is inconsistent with previous study (Zhang, 2004) that population density only contributes to work trips but not non-work trips. It is reasonable that job density dominates work trips with a potential rigid demand of transit commute and population density dominates recreation and shopping trips that these social activities mostly happen near home and with a place with lots of people.

Apart from the major concern of built environment on mode choice, other socioeconomic or trip-based factors have consistent results as well. Income factor in all models has slight impact on mode choice between automobiles and public transport. For age concerns, it is consistent that elderly people are more willing to drive a car than ride a bus or subway in all scenarios. The

availability of a car is generally the top factor (with a coefficient almost over 3 in all scenarios) for deciding whether to take public transport or drive except for fewer cases that higher job density has a higher contribution. For number of people in a trip, 2 to 5 people is always the group with the highest rate of use automobiles in all cases and the groups over 5 are mostly slightly against tips by public transport and in the case of work trips are mostly favored and specifically to bus trips rather than rails. For trip distance, 1 mile is demonstrated to be a lower threshold distance for taking public transport. It is reasonable that the waiting time might be longer than the time walking to the destination. The upper threshold is blurred from the study.

In all, the factors included in the model show least multicollinearity and mostly play statistically significant roles on the mode choice decision. With the limits of data source and model functions, I fail to include public transport accessibility index into the analysis which might counteract some degrees of effects on density variables and might better explain the trend of population density ceiling of 20 residents per acre; the case of more favored rail trips than bus trips, etc. And self-attitudinal factors shall also be included in future analysis as it may play a more important role than built environment (Weber and Kwan, 2003; Prevedouros, 1992; and Kitamura et al., 1997).

8. Policy Implications

Based on the conclusions above, here are implications for the New York Metropolitan Area to improve in order to increase the ride share of public transport to a higher level in the future.

(1) Transit Oriented Development implementation

The mode share of public transport in New York City has reached 31% and together with the mode of walking and biking it rises to as high as 65%. It is a very high level of public transport use throughout the world. However, the sum of public transport and walking/biking mode share for the whole region drops to only 28% and the rate drops to 16% if only considering places other than New York City. For those places with much lower public transport use, transit oriented development (TOD) would be an effective solution.

As higher density mostly contributes to more public transport trips, the ideas would be to increase density to support public transport. While it is impossible to increase the density suddenly for all places, places close to existing transit corridors are within first priority group. The model results of higher density contributes more than higher population density could be learned to put more office buildings and other commercial spaces for job opportunities around major transit hubs and residential buildings could be put a little bit farther away than those office and commercial buildings to the stations.

Though it is remain to be proved true or not that the reference criteria of population density over

20 residents per acre and job density over 100 jobs per acre, it is a new direction of research and a more solid way of suggestions with detailed figures. If the base requirement threshold of TOD density exists, it would be helpful on planning a new TOD site with a good tool of target control.

(2) Commuter rails

Specifically for commuter rails, the major stations along the lines are the best choice of sites to implement TOD. The model results of the comparison between rail and bus exhibit that railroad would achieve a more effective increase on ridership by the increase of contributing factors. The marginal benefit from the investment will be the highest for commuter railroads among all modes of public transport. Therefore the hub stations which already have more activities and passengers attractions will realize TOD first and then become a hub to encourage additional bus trips to other places and help implement more TOD sites.

(3) Subways

Subways have played a crucial role for making the base of a high mode share of public transport trips in New York City. It is also demonstrated from the models that higher density built environment has a more effective way on more subway trips than bus trips. However, based on the complexity of New York City underground and the lack of funding for constructing a new subway line, the new subway lines may not be feasible in New York City. For other places, there is not yet a town has a higher enough density to support subway operation, the role for increasing more public transport trips by subways is limited temporarily.

(4) Buses

Though it is not as effective as subways or commuter rails on increasing more public transport trips, buses are crucial for the current situations to either provide a supply for commuter rails through collection and dispersion or provide a supplement to subways for a place with the demand of new subway service but restricted by technical or financial obstacles. And the model results can be interpreted that the lower coefficient values are attributed to the currently less effort put into the buses than the rails. Both stop spacing and service frequency of buses are much more inefficient compared to rails now. There shall be more effort concentrated into the improvement of bus service and the connection between bus and rail for promoting future's more transit-oriented travel behavior.

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